26th International Congress of Mechanical Engineering
COBEM 2021
ABCM Associação Brasileira de Engenharia e Ciências Mecânicas
November 22-26, 2021, Virtual Congress, Brazil

COB-2021-2312
PARAMETRIC PROBABILISTIC MODEL FOR PREDICTING CREEP REMAINING USEFUL LIFE

Victor Vieira Maudonet
Rio de Janeiro State University – UERJ, Rio de Janeiro, Brazil
victor.maudonet@uerj.br

Carlos Frederico Trotta Matt
Electric Power Research Center – CEPEL, Rio de Janeiro, Brazil
cfmatt@cepel.br

Americo Cunha Jr
Rio de Janeiro State University – UERJ, Rio de Janeiro, Brazil
americo.cunha@uerj.br

Abstract. *The creep phenomenon, associated with a time-dependent progressive deformation of a material under stress and high temperatures, is of great industrial interest since these are typical operating conditions in several industries. Thus, a safe forecast of the life in creep is a critical phase in the design of equipment that operates at high temperatures, essential for the success of these projects. Although several parametric methods are available to quantify the creep deformation, most of them use deterministic approaches, that do not consider the remarkable dispersion of experimental creep data. This inevitably leads to deterioration in the predictive capacity of these models. Aiming to correct this deficiency, this work employs a parametric probabilistic approach to quantify the uncertainties associated with the parameters of parametric models for predicting creep remaining life. A probabilistic model, constructed with aid of the statistical information extracted from experimental data, is used to describe the underlying parametric uncertainties, and Monte Carlo method is used to propagate these uncertainties through the predictive model. From that, it is possible to evaluate the forecasting capacity of each model and define safe limits with known confidence levels.*

Keywords: *creep modeling, structural integrity, uncertainty quantification, global sensitivity analysis*

1. INTRODUCTION

The current work proposes a probabilistic uncertainty quantification approach to predict high-temperature creep in metallic components. A variety of parametric methods have been developed to quantify creep in high-temperature applications. These parametric methods play a key role during the design and operation of high-temperature components. Design codes for metallic components subjected to the creep aging phenomenon are intended to assure a specific life. Current parametric methods and structural integrity codes employ deterministic approaches, which most commonly rely on conservatism to account for uncertainty. Model-parameter and model uncertainties induced by modeling errors as well as measurement uncertainties in creep predictive models and creep data are not rigorously taken into account and still depend on subjective engineering judgments (N Roya and Ghoshc, 2010). By using excessive conservatism, one can be despising the issue of insufficient data to characterize material properties for long-term conditions, the use of extrapolations beyond the short-term experimental testing ranges, the inherent large dispersion in creep data, difficulties associated with the mathematical modeling of creep phenomenon and yet, in some cases, unknown, lack understanding of the underlying failure mechanisms and their interactions (Zentuti *et al.*, 2017). Formally considering these aspects becomes necessary as the materials progress through their rupture time, and the focus shifts from not only predict the residual life whilst promote an acceptable level of safety but also arguing for life extension what needs the reduction of conservatism. This shift requires a parallel change from a deterministic perspective to a probabilistic perspective, as bility and risk assessment become the main drivers (Vojdania *et al.*, 2018). Therefore, it is necessary to quantify the uncertainties to calculate the probability of failure, which fall beyond the purposes of traditional deterministic approaches, while probabilistic paradigms are well equipped for such applications.

Limited work has been developed in the area of probabilistic high-temperature applications, so this paper presents a complete, though non-exhaustive, methodology for the implementation of probabilistic methods for assessing creep remaining life based on parametric creep life prediction models (Zentuti *et al.*, 2017). This methodology is intended to be divorced from any specific code or procedure and can be translated to any creep structural integrity application. The proposed methodology implements Monte Carlo simulations Cunha Jr *et al.* (2014) to estimate probabilities of interest. In essence, the Monte Carlo simulation aggregates the uncertainties associated with input parameters through the parametric creep models to estimate the uncertainty in the output parameter, the rupture time, based on which probability estimates of interest can be computed. Due consideration is given to various issues: the statistical treatment of the raw experimental data, statistical model construction, sampling, inclusion of input parameter correlations, treatment of parameter uncertainties, and sensitivity analyses. The final stage of the proposed methodology is concerned with estimating the probability of failure, raising statistics, and thereby direct the way towards formulating a probabilistic creep methodology for safe operation in high-temperature conditions. Thus, the motivations for developing such a methodology are justifying a perspective shift from the currently followed deterministic procedures toward probabilistic procedures, identification of various sources of uncertainty and their characterization through probabilistic analyses, the need for assessing the appropriateness of probabilistic techniques and their merits as compared with the currently used deterministic methods.

2. LARSON-MILLER CREEP MODEL

Deterministic methods have been developed to predict the long-term creep properties based on short-term creep experiments, these deterministic models are capable to reduce the time scales and costs necessary to obtain these long-term data. These methods establish a procedure whereby short-term creep data can be extrapolated using a time-temperature parameter. This technique is based on the assumption that all creep-rupture data, for a specific material, can be superimposed to generate a single ‘master curve’ wherein the stress is plotted against an empirical parameter that contains and combines time and temperature. From this master curve, which can only be constructed using available short-term creep data, extrapolation to longer times can then be calculated. However, due to the large dispersion of experimental data on creep, different predictions often occur when using experimental data obtained under the same experimental condition. Therefore, these uncertainties need to be taken into account to produce a safe life prediction from a broader approach. The application of these parametric methods represents a crucial step in the initial design phase of equipment that operates at high temperatures to guarantee a specific service life determined by the code and this reinforces the need for these models to be applied from a probabilistic perspective. Generally, these design codes define maximum allowable stress that can exist in a component during the anticipated design life. This allowable design stress is usually based on the rupture stress required to give the expected design life (Cane and Aplin, 1994).

The Larson-Miller approach is one of the most parametric methods used to predict the rupture time for the creep of metals. It has been developed from Arrhenius relation at constant stress and thus, a constant stress exponent (n), but at a variable value of temperature (T) and the activation energy for creep (Q_c), which gave the final form of this relation as (Larson and Miller, 1952):

$$P_{LM}(\sigma) = T \, \left(C + \log_{10} t_r\right) \, , \tag{1}$$

where C and P_{LM} are the Larson-Miller constant and parameter, respectively. The parameter, P_{LM}, can be used to superimpose the family of rupture curves into a single master curve (Penny and Marriot, 1995). Plotting $\log_{10} t_r$, the rupture time logarithm, against the inverse of temperature $1/T$ at a constant stress σ, for some experimental data gave straight lines of slope P_{LM} and an intercept of $-C$ (F Monkman, 1956).

Larson and Miller took one step further in their original proposal, suggesting that the value of the constant C could be taken as 20 for many metallic materials (Gilbert *et al.*, 2007). However, it was found that the value of this constant varies from one alloy to another and is also influenced by factors such as cold-working, thermo-mechanical processing, phase transitions, and/or other structural modifications (Gilbert *et al.*, 2007). Most applications of the Larson-Miller parameter are made by first calculating the value of C that provides the best fit of the raw data, which means that C is treated as a fitting constant based on a ‘trial and error’ method instead of being a physically meaningful constant (Gilbert *et al.*, 2007). Therefore, the requirement of a physical realism of extrapolation was not completely fulfilled by this method.

Given this evidence, it is clear that traditional deterministic procedures are not sufficient to safely apply this parametric model in predicting creep remaining life. Thus, a move towards developing a probabilistic perspective that can identify various sources of uncertainty and their characterization through probabilistic analyses is needed.

3. UNCERTAINTY QUANTIFICATION FRAMEWORK

Figure 1 shows a schematic illustration of the complete uncertainty quantification framework, which is very similar to those used in (Nispel *et al.*, 2021) and (Dias *et al.*, 2019, 2018).

In the first stage of the uncertainty quantification framework, the main objective is to establish the relationship between the empirical parameter (P_{LM}) of the deterministic creep model and the mechanical stress (σ). So first, raw experimental data is treated to reduce the effect of possibly spurious outliers that may skew the analysis. This is done using the winsorizing technique by limiting extreme values. This strategy is based on set all outliers to a specified percentile of the data; a 95 winsorization would see all data below the 5^{th} percentile set to the 5^{th} percentile, and data above the 95^{th} percentile set to the 95^{th} percentile. After this data processing, the process of identifying the relationship between the

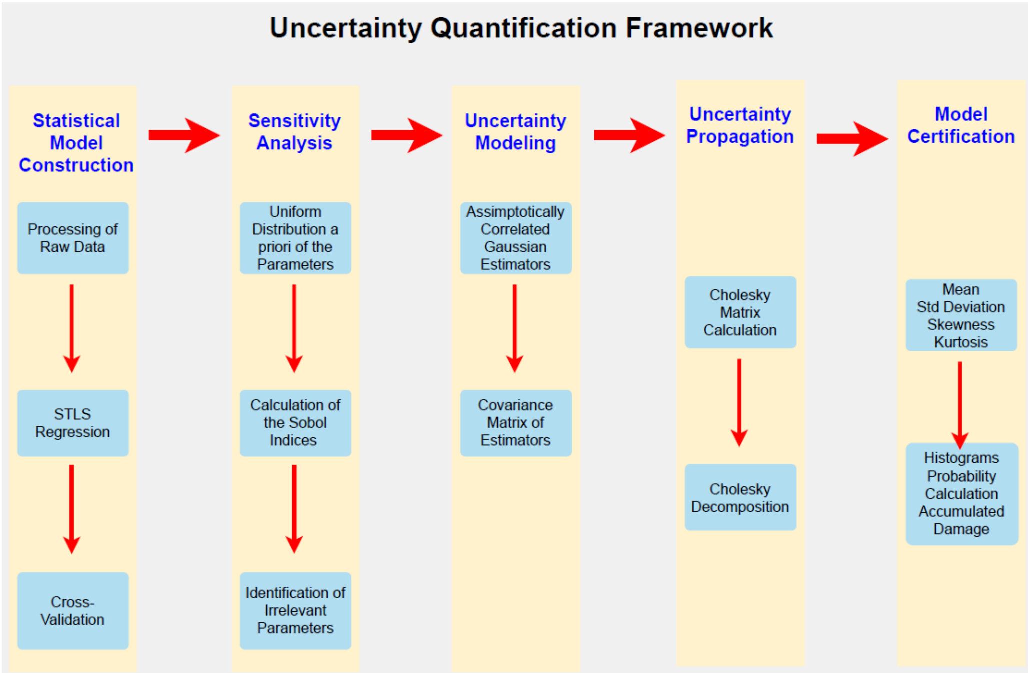

Figure 1: Schematic illustration of the probabilistic uncertainty quantification framework

parameters of each creep model begins. For this, in a data-driven perspective, a sparse regression type called sequential threshold least-square (STLS) was used in conjunction with a cross-validation (Brunton and Kutz, 2019). The STLS will allow the polynomial relationship to be identified without presumptions by testing polynomials up to degree 8 and establishing threshold values of $\lambda = 0.1$ and $\lambda = 0.01$ for the coefficients of the polynomial's powers, thus eliminating the irrelevant powers and defining the best fit based on a rational criterion. Cross-validation is used to assess the predictive capacity of each polynomial to estimate how accurately they perform in practice and select the best polynomial based on the root mean squared error (RMSE) criterion (Knafl and Ding, 2016). To do this, cross-validation involves partitioning the experimental data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set). After that, the sum of the square of the residuals is calculated, the experimental data is shuffled and the partitioning process is repeated. Each degree of polynomial undergoes 100 iterations so that in the end there is a ranking with 800 evaluations. The polynomial that has the lowest RMSE value will be selected.

In the second stage of the framework, a global sensitivity analysis is performed to identify the main sources of variability in the model output introduced by the input parameters. When a large number of possible input parameters is considered, sensitivity analysis provides a tool for identifying which should be considered with the most care, and which could be omitted from the probabilistic procedure all together (Zentuti *et al.*, 2017). This is done by calculating the sensitivity indices, which are measures of the contributions of each variability in the input parameter toward the overall variability in the output. The sensitivity indices used in this work are the Sobol indices. There are various approaches for calculating the sensitivities indices, in this work is used the Monte Carlo method (MC) (Kroese *et al.*, 2011; Cunha Jr *et al.*, 2014) and Polynomial Chaos Expansion (PCE) (Ghanem and Spanos, 2003; Xiu, 2010). The Monte Carlo method is used as the reference and the PCE is used to prevent cancellation errors in the calculation of higher-order indices and due to the low computational cost of the method (Sudret, 2008; Crestaux *et al.*, 2009; Marelli and Sudret, 2014). For the MC it is used 10,000 samples and for the PCE coefficients, calculations use the Ordinary Least-Squares method, with 1,000 samples and a maximum degree of 10.

The third stage of the framework deals with the modeling of uncertainties which is a fundamental step for the quantification of uncertainties and serves to understand how the variability of the input parameters behave, and this is done by determining the probability distribution function of each parameter. To this end, it is necessary to use rational criteria to determine the probability distribution function and thus avoiding the use of assumptions that may mask the true behavior of the variability (Soize, 2017; Cunha Jr, 2017). However, in a model, not all input parameters can be considered random variables due to their nature or the way the experiment is performed. In the creep model treated in this work, the temperature and the mechanical stress are treated as control variables due to the way the creep experiment was conducted during the production of the experimental data (in a creep test, temperature and mechanical stress are set to determine the experimental conditions) and therefore it is not necessary to quantify the uncertainties associated with these input parameters (Evans, 2001). Four different experimental conditions are investigated in this work to simulate the operational field of a power plant and identify how the variation in mechanical stress and temperature affect the variation of the rupture time.

On the other hand, the polynomial coefficients that define the relation between the empirical parameter (P_{LM}) and the mechanical stress (σ), and the empirical constant of each model (C) are treated as random variables. By the Central Limit Theorem, the estimators of the foregoing random variables are asymptotically Gaussian; therefore, a multivariate Gaussian distribution is chosen to describe their joint statistics. Denoting by $\mathbf{X}$ the random vector whose components are the polynomial coefficients and the empirical constant C, their joint PDF is the well-known multivariate Gaussian PDF given by

$$p_{\mathbf{X}}(\mathbf{x};\boldsymbol{\mu}_{\mathbf{X}},\boldsymbol{\Sigma}_{\mathbf{X}}) = \frac{1}{(2\pi)^{\frac{n}{2}}\sqrt{\det\boldsymbol{\Sigma}_{\mathbf{X}}}}\exp\left\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_{\mathbf{X}})^T\boldsymbol{\Sigma}_{\mathbf{X}}^{-1}(\mathbf{x}-\boldsymbol{\mu}_{\mathbf{X}})\right\}\,, \tag{2}$$

where n is the number of random variables selected by the global sensitivity analysis; and $\boldsymbol{\mu}_{\mathbf{X}}$ and $\boldsymbol{\Sigma}_{\mathbf{X}}$ denote, respectively, the mean vector and covariance matrix for the random variables selected by the global sensitivity analysis. The mean vector is the least-squares estimator of the input parameters selected by the global sensitivity analysis. The covariance matrix $\boldsymbol{\Sigma}_{\mathbf{X}}$ is computed from the following expression (Smith, 2013):

$$\boldsymbol{\Sigma}_{\mathbf{X}} = \sigma^2\,(\mathbf{A}^T\mathbf{A})^{-1}\,, \tag{3}$$

where σ^2 is the variance of the residual between the estimated rupture time and the experimental rupture time and $(\mathbf{A}^T\mathbf{A})^{-1}$ is the inverse matrix that appears in the matrix equation that gives the least-squares estimators for the selected input parameters by the global sensitivity analysis. Model-parameter uncertainty is thus fully described by the multivariate Gaussian PDF in Eq. (2), the mean vector $\boldsymbol{\mu}_{\mathbf{X}}$ and covariance matrix $\boldsymbol{\Sigma}_{\mathbf{X}}$. The next step is to quantify how model-parameter uncertainty affects the uncertainty of the output quantities of interest (QoIs) computed from the parametric creep model. Here, creep rupture time is the output QoI.

The uncertainty propagation stage, the last stage, consists of generating samples of the input parameters of the model from their respective probability distribution functions and using them to calculate samples of the quantity of interest (t_r) using the model. To perform this analysis the Monte Carlo Method is used with 10,000 samples, we can divide this method is three general steps: pre-processing, process, and post-processing. In the pre-processing step to generate the samples of the input parameter of each model, the Cholesky decomposition is used due to the correlation between the input parameters of the models. So, the covariance matrix of each model is decomposed to give a lower-triangular matrix. Applying this matrix to a sample vector of Gaussian uncorrelated samples and adding to the mean vector of the input parameters produces a sample vector with the covariance properties of the system being modeled. Now, in the process step, the solution of each creep model is calculated from the respective generated samples of the input parameters, so that in the end 10,000 samples of the rupture time, t_r, are generated. Lastly, in the post-processing step, several analyzes are performed to ensure that the probability distributions obtained are representative of the physical reality of the investigated phenomenon and to describe the behavior of the variability of the rupture time (t_r). In this sense, the rupture time histogram is produced for the four operating conditions investigated for each creep model, and some statistics are calculated, such as the mean, standard deviation, coefficient of variation, skewness, and kurtosis. These statistics are compared with experimental results for validation.

4. RESULTS AND DISCUSSION

At the stage of construction of the statistical model, applying the winsorizing technique to raw experimental data to securely establish the relationship between the empirical parameter and the mechanical stress for each creep model makes all data below the 5$^{\text{th}}$ percentile set to the 5$^{\text{th}}$ percentile, and data above the 95$^{\text{th}}$ percentile set to the 95$^{\text{th}}$ percentile. After this treatment of the experimental data, it is implemented the sequential threshold least-square regression (STLS) in conjunction with cross-validation. The STLS eliminates irrelevant polynomial powers based on the threshold values $\lambda = 0.1$ and $\lambda = 0.01$. The cross-validation technique is used to assess the predictive capacity of each polynomial produced by the STLS method with 100 iterations. This means that for each new polynomial produced by the STLS method, the experimental data is shuffled and divided into training data and test data. The training data is used by the STLS method and the test data is used to rank the predictive quality of each polynomial based on the root mean square error (RSME), that is, the best polynomial to represent the relationship between the Larson-Miller parameter and the mechanical stress is the one with the lowest RSME value. At the end of the process, 800 polynomials will be generated and ranked. The Table 1 shows the mean value of each polynomial coefficient for each regression degree for all 100 cross-validation iterations.

It can be seen that polynomials up to degree 3 are selected by applying the threshold value of 0.01, which is compatible with the behavior of the experimental points of the Larson-Miller graph.

The polynomial selected as representative of the relationship between the Larson-Miller parameter and the mechanical stress is the one that has the lowest value of the sum of the residual square. The smallest RSME value is 459.811 which corresponds to the polynomial $22205.0 - 12.0\sigma$, showing that the relationship is an affine function:

$$P(\sigma) = 22205.0 - 12.0\,\sigma\,. \tag{4}$$

Table 1: The mean value of each polynomial coefficient for each regression degree for all cross-validation iterations.

Polynomial Degree	Threshold Value $\lambda = 0.1$	$\lambda = 0.01$
1	$22202.0 - 12.0\,\sigma$	$22205.0 - 12.0\,\sigma$
2	$22190.0 - 11.9\,\sigma$	$21580.0 - 11.7\,\sigma$
3	$21863.0 - 4.8\,\sigma$	$21876.0 - 4.9\,\sigma - 0.04\,\sigma^2$
4	$22502.0 - 23.9\,\sigma + 0.13\,\sigma^2$	$22484.0 - 23.2\,\sigma + 0.13\,\sigma^2$
5	$22112.0 - 9.3\,\sigma$	$22127.0 + 35.1\,\sigma - 0.8\,\sigma^2$
6	$21160.3 + 34.5\,\sigma - 0.78\,\sigma^2$	$21158.0 - 9.8\,\sigma - 0.04\,\sigma^2$
7	$21152.0 + 35.0\,\sigma - 0.79\,\sigma^2$	$20873.0 + 50.86\,\sigma - 1.12\,\sigma^2$
8	$19117.0 + 167.9\,\sigma - 4.17\,\sigma^2$	$18747.0 + 190.3\,\sigma - 4.7\,\sigma^2 + 0.06\,\sigma^3$

Figure 2 shows the plot of the polynomial relationship between the Larson-Miller parameter and the mechanical stress with the experimental data.

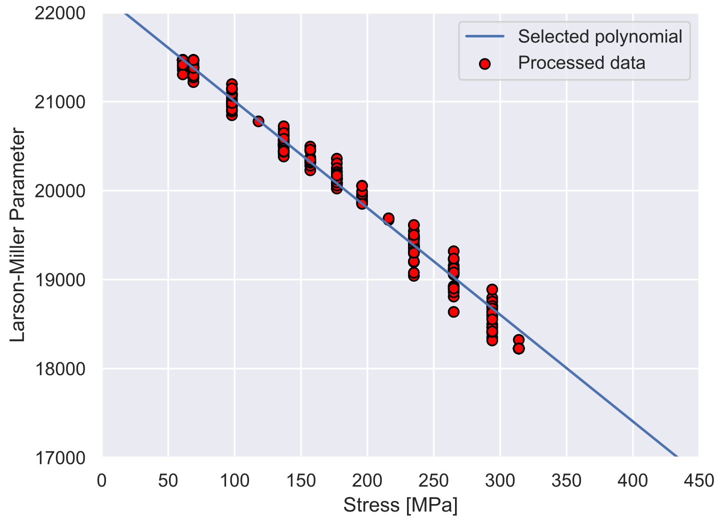

Figure 2: The polynomial relation between the Larson-Miller parameter and the mechanical stress.

In the global sensitivity analysis stage, several calculations are conducted to assess the sensitivity of the output results towards various input conditions for the creep model investigated. Firstly, sensitivity measures are calculated using the two approaches to assess the dominance, i.e., the relative importance of all random inputs parameters: Monte Carlo method and Polynomial Chaos Expansion. The MC is used as the reference and the PCE is used to prevent cancellation errors in the calculation of higher-order indices and due to the low computational cost of the method. For the MC it is used 10,000 samples and for the PCE coefficients calculations, it is used the Ordinary Least-Squares method, with 1,000 samples and a maximum degree of 10. The complete set of quantitative sensitivity analysis results is shown in Figures 3 which indicate that the coefficients a_0, σ, T, and C dominate the probabilistic rupture time results for the Larson-Miller model. Another important result obtained is the relevance of the interaction between the input parameters, showing how important it is to carefully select the operational conditions and how a small alteration of some of these parameters can have a drastic effect on the material rupture time.

First, what can be observed is that the MC method and the PCE converged, resulting in values very close for the Sobol indices for both methods. In addition, one can see that the isolated effect of the variability of the input parameters does not significantly affect the response, since the values of the first-order Sobol indexes of the parameters are less than 0.1. What is relevant to the rupture time is the strong effect of interaction between the parameters. The Sobol indices of parameter a_1 did not obtain relevant values, indicating that the variability of this parameter is not capable of affecting the response and, therefore, the model can be reduced and this parameter can be eliminated from the subsequent analyzes.

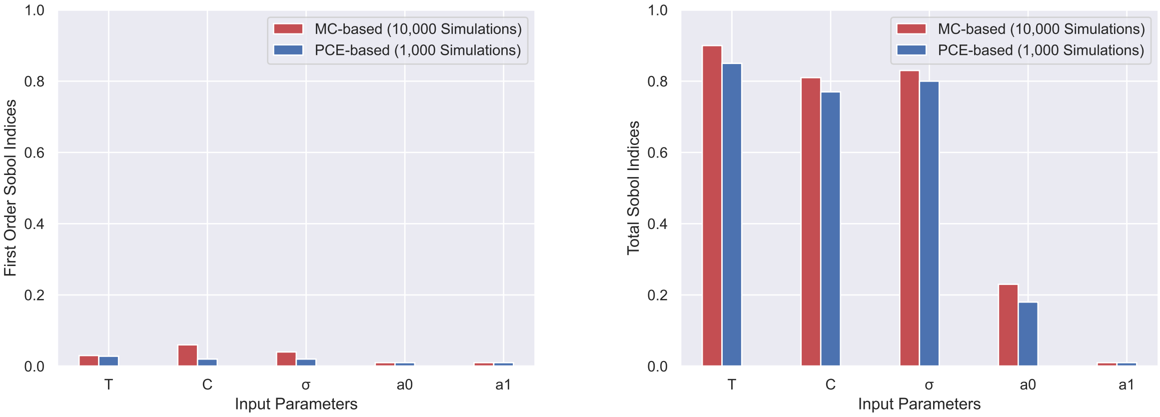

Figure 3: First (left) and total (right) order Sobol indices.

Table 2: The four selected experimental conditions.

Experimental Condition	Stress [MPa]	Temperature [^oC]
1	137	550
2	333	550
3	47	650
4	137	650

Then, by generating 10,000 samples of the input parameters from their joint probability distribution and propagating the uncertainties of the input parameters in the Larson-Miller model for the four selected operating conditions shown in Table 2, it is possible to obtain 10,000 samples of the rupture time and produce histogram for each experimental condition.

Figures 4 shows the histogram of the 10,000 samples of the rupture time (t_r) obtained after the propagation of the uncertainties of the input parameters in the Larson-Miller model for the four operational conditions. To better understand the behavior of the uncertainties associated with the rupture time, some statistics were also calculated, such as the mean, standard deviation, skewness, kurtosis, and variation coefficient. All of these statistics are condensed in Table3 according to their respective experimental condition for comparison.

Table 3: Statistics for the rupture time for all the operational conditions.

	Condition 1	Condition 2	Condition 3	Condition 4
Mean	134,810h	1,774h	10,574h	106h
Standard deviation	337,025h	3,140h	21,888h	240h
Skewness	3.0	2.2	2.2	2.9
Kurtosis	9.2	4.2	4.2	8.7
Coefficient of Variation	225%	177%	207%	219%

From the analysis of histograms, it is then possible to perceive the remarkable experimental dispersion of the rupture time evidenced by the histogram that reveals an exponential distribution. In addition, the exponential behavior of the probability distribution obtained through statistical methods corroborates the physics of the phenomenon, which is exponential. It can also be observed that the rupture time can vary dramatically with the variation of operating conditions and therefore deserves to be selected and monitored very carefully.

5. CONCLUSION

This paper introduces a complete probabilistic framework that can be implemented to any structural integrity application, and this was done using a high-temperature creep example where a parametric model is applied to predict remaining life for contextualization and demonstrating the use of the framework. Various probabilistic methods and concepts were

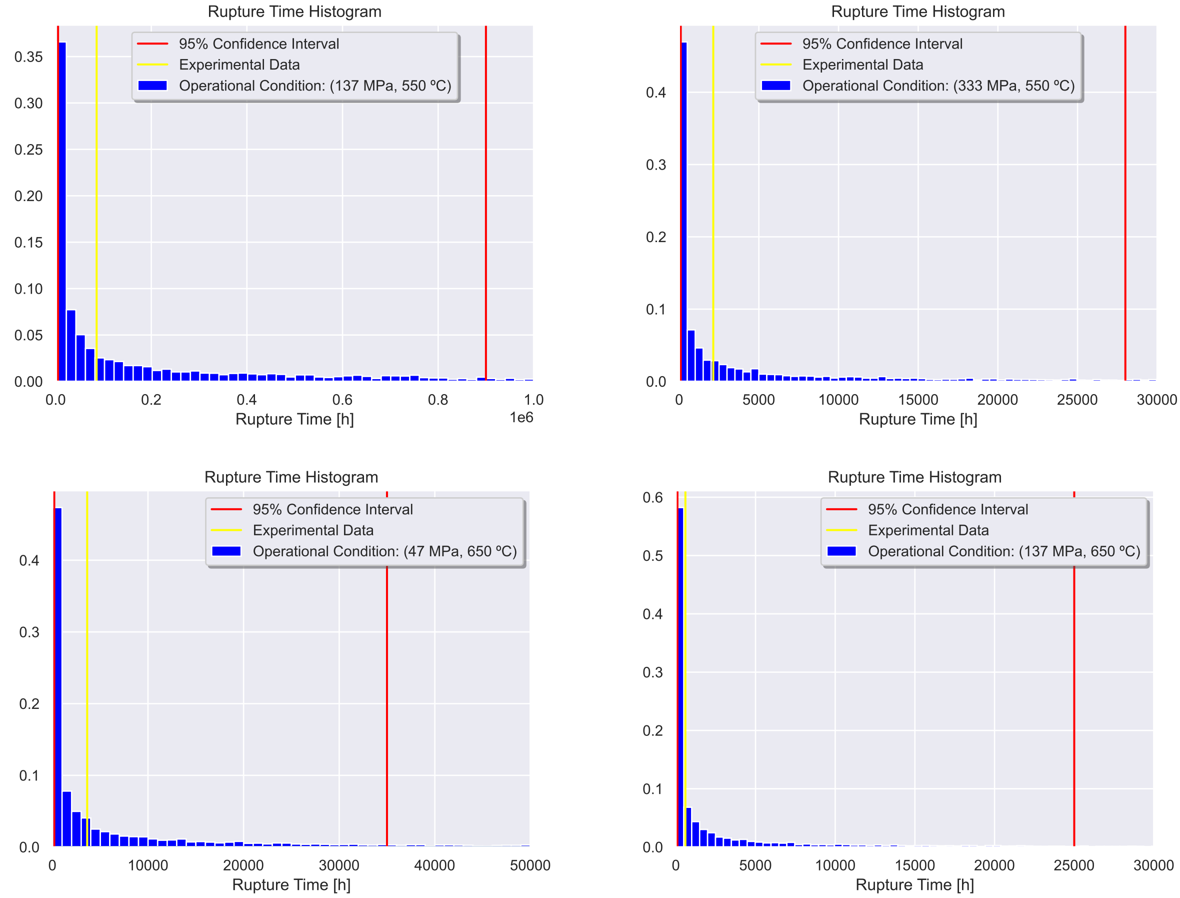

Figure 4: Rupture time histogram for Larson-Miller model for the four operational conditions.

used, the most relevant of them are: Monte Carlo Simulations, Cholesky decomposition for sampling, sensitivity analysis, correlations between input parameters, treatment of input parameters uncertainties, and statistics.

Probabilistic procedures should not be seen as alternatives for traditional deterministic procedures, since the probabilistic perspective is armed with several techniques that allow to identify and quantify all the uncertainties inherent in the model and does not use excessive conservatism to compensate for the lack of knowledge, they should be seen as an extended approach equipped with more tools that apply a different view to deal with the problem. Thus, the probabilistic methods can be considered a step beyond conventional deterministic methods, that have spread through the combined use of statistical techniques and physical models for failure prevention, driven by advances in scientific computing and the volume of data generated by the world. To implement a probabilistic framework to structural integrity problems, it is necessary to understanding the physics of the model and data for the construction of the statistical model of the inputs parameters, has appropriate experimental data available, be familiar with probabilistic approaches and statistical concepts, be able to relate these to a physical problem of interest and computational experience in producing efficient algorithms.

Thus, this paper aims to strengthen the links between probabilistic and statistical methods and the general structural integrity community especially in the area of high-temperature applications. In this sense, the path is to establish a standard of knowledge of these techniques in the community, so those probabilistic methods are used more often so that preventions are carried out with greater reliability and safety.

6. ACKNOWLEDGEMENTS

The authors thank the financial support received from Electric Power Research Center – CEPEL, Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001, and the Carlos Chagas Filho Research Foundation of Rio de Janeiro State (FAPERJ) under the following grants: 211.304/2015, 210.021/2018, 210.167/2019, and 211.037/2019.

7. REFERENCES

Brunton, S.L. and Kutz, J.N., 2019. *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*. Cambridge University Press.

Cane, B. and Aplin, P., 1994. "Creep life assessment methods". *The Journal of Strain Analysis for Engineering Design*, Vol. 29, pp. 225–232.

Crestaux, T., Le Maître, O. and Martinez, J., 2009. "Polynomial chaos expansion for sensitivity analysis". *Reliability Engineering & System Safety*, Vol. 94, pp. 1161–1172.

Cunha Jr, A., 2017. "Modeling and Quantification of Physical Systems Uncertainties in a Probabilistic Framework". In S. Ekwaro-Osire, A.C. Gonçalves and F.M. Alemayehu, eds., *Probabilistic Prognostics and Health Management of Energy Systems*, Springer, Cham, pp. 127–156.

Cunha Jr, A., Nasser, R., Sampaio, R., Lopes, H. and Breitman, K., 2014. "Uncertainty quantification through Monte Carlo method in a cloud computing setting". *Computer Physics Communications*, Vol. 185, p. 1355 – 1363.

Dias, J.P., Ekwaro-Osire, S., Cunha Jr, A., Alemayehu, F.M., Dabetwar, S. and Nispel, A., 2018. "A parametric probabilistic approach to quantify uncertainties in a non-linear cumulative fatigue damage model considering limited data". In *Twelfth International Conference on Fatigue Damage of Structural Materials (ICFDSM 2018)*. Hyannis, United States.

Dias, J.P., Ekwaro-Osire, S., Cunha Jr, A., Dabetwar, S., Nispel, A., Alemayehu, F.M. and Endeshaw, H.B., 2019. "Parametric probabilistic approach for cumulative fatigue damage using double linear damage rule considering limited data". *International Journal of Fatigue*, Vol. 127, pp. 246–258.

Evans, R.W., 2001. "Creep and constant strain rate deformation". *Encyclopedia of Materials: Science and Technology (Second Edition)*, Vol. 94, pp. 1750–1757.

F Monkman, N.G., 1956. "An empirical relationship between rupture life and minimum creep rate in creep rupture tests". *ASTM Proceedings*, Vol. 56, pp. 593–620.

Ghanem, R.G. and Spanos, P.D., 2003. *Stochastic Finite Elements: A Spectral Approach*. Dover Publications, 2nd edition.

Gilbert, J., Long, Z. and Ningileri, S., 2007. *Application of Time-Temperature-Stress Parameters to High Temperature Performance of Aluminium Alloys*. The Minerals, Metals & Materials Society.

Knafl, G.J. and Ding, K., 2016. *Principles of Data Science*. Packt Publishing.

Kroese, D.P., Taimre, T. and Botev, Z.I., 2011. *Handbook of Monte Carlo Methods*. Wiley.

Larson, F. and Miller, J., 1952. "A time-temperature relationship for rupture and creep stresses". *Transactions of the American Society of Mechanical Engineers*, Vol. 74, pp. 223–249.

Marelli, S. and Sudret, B., 2014. "UQLab: a framework for uncertainty quantification in MATLAB". In *Proc. 2nd Int. Conf. on Vulnerability, Risk Analysis and Management (ICVRAM2014), Liverpool, United Kingdom*. p. 2554–2563. doi:10.1061/9780784413609.257.

N Roya, S.B. and Ghoshc, R., 2010. "Stochastic aspects of evolution of creep damage in austenitic stainless steel". *Materials Science and Engineering A*, Vol. 527, pp. 4810–4817.

Nispel, A., Dias, J.P., Ekwaro-Osire, S. and Cunha Jr, A., 2021. "Uncertainty quantification for fatigue life of offshore wind turbine structure". *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems Part B: Mechanical Engineering*, Vol. , p. in press.

Penny, R. and Marriot, D., 1995. *Design for Creep*. Chapman & Hall.

Smith, R.C., 2013. *Uncertainty Quantification*. SIAM.

Soize, C., 2017. *Uncertainty Quantification: An Accelerated Course with Advanced Applications in Computational Engineering*. Springer.

Sudret, B., 2008. "Global sensitivity analysis using polynomial chaos expansions". *Reliability Engineering & System Safety*, Vol. 93, No. 7, pp. 964–979.

Vojdania, A., Farrahia, G., Mehmanparastb, A. and Wangc, B., 2018. "Probabilistic assessment of creep-fatigue crack propagation in austenitic stainless steel cracked plates". *Engineering Fracture Mechanics*, Vol. 200, pp. 50–63.

Xiu, D., 2010. *Numerical Methods for Stochastic Computations: A Spectral Method Approach*. Princeton University Press.

Zentuti, N.A., Booker, J.D. and Bradford, R.A.W., 2017. "A review of probabilistic techniques: towards developing a probabilistic lifetime methodology in the creep regime". *Materials at High Temperatures*, Vol. 34, pp. 333–341.

8. RESPONSIBILITY NOTICE

The authors are solely responsible for the printed material included in this paper.